

The Impact of Aggregate Changes in Fundamental Analysis on Macroeconomic Forecasts



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1. Introduction

Macroeconomic forecasts are crucial for the well-being of the economy as they provide stakeholders with information on the macro as well as micro level to optimise resource allocation, minimise waste and ensure a stable business environment. Thus, this thesis attempts to use aggregate accounting information to contribute to the enhancement of macroeconomic forecasts.

Several potential user groups for macroeconomic forecasts exist. Central banks intend to foresee future developments of the economy to set a desired level of inflation by lowering (raising) interest rates to incentivise (disincentivise) investors during recessions (upswings) to keep the economy close to equilibrium (Carlin & Soskice, 2015). Individuals and entrepreneurs intend to benefit from booms or reduce their downside risk. Beyond, employers utilise forecasts to set benchmarks for wage setting purposes and business planners must be informed about the current stage of the business cycle to evaluate the sustainability of existing or new product lines (Carlin & Soskice, 2015). Therefore, it is crucial to continuously refine macroeconomic forecast models.

Konchitchki and Patatoukas (2014) started the ball rolling by investigating the usefulness of aggregate accounting data on macroeconomic forecasting and find financial performance ratios to contain predictive power for subsequent macroeconomic growth. Their idea is intended to be further developed and tested by highlighting the usefulness of the F-Score (Piotroski, 2000), a financial performance metric created to assess firms' financial fundamentals. The F-Score is composed of so-called binary signals that sum up to a final score. Hence, aggregate changes in Total F-Score, as well as its components (Partial F-Scores), serve as explanatory variables to predict subsequent macroeconomic growth.

As the name suggests, macroeconomic forecasts are forward looking, a characteristic necessary for being valuable. For example, when regarding monetary policy, the economy displays a lagged reaction of at least six months with the consequence that macroeconomic forecasts, as well as monetary policy, must be forward looking to compensate for the delayed response in the economy

(Carlin & Soskice, 2015). Nevertheless, this characteristic comes at the cost of imprecision, as even the most thorough analysis and forecast is incapable to perfectly predict the future. This inevitable imprecision leads to at least partially faulty resource allocation and thus to an overall loss to the economy. To minimise this imprecision and its associated costs, macroeconomists attempt to improve forecasting models and conceive new ideas to reduce forecasting errors. One such attempt is the research conducted by Konchitchki and Patatoukas (2014), who investigate a relatively unexplored approach by utilising financial statement analysis for macroeconomic predictions and analyse the extent to which the Survey of Professional Forecasters (SPF) by the Federal Reserve Bank of Philadelphia, incorporates this type of information.

Financial statement analysis summarises the economic consequences of a company's business activities. Accounting standards such as the US GAAP intend to provide a framework for companies to deal with the trade-off between overly loose and overly tight regulations. These standards limit the company's ability to inaccurately represent their financial position and facilitate comparisons between various firms (Kieso, Weygandt & Warfield, 2014; Palepu, Healy & Peak, 2016). Furthermore, companies' financial positions appear to be persistent over time, making them predictable and therefore valuable as incremental information for macroeconomic projections (Soliman, 2008). Konchitchki and Patatoukas (2014), advertise the usefulness of aggregate accounting data of the largest corporations in the United States (US). Their study makes use of the fact that listed firms represent a large part of the US economy, and thus changes in their financials are informative for overall economic activity. This simplicity and thus its low-cost characteristics is the most significant strength of their methodology, as only a small number of firms must be analysed.

Building up on this research, this thesis attempts to further illuminate the usefulness of financial statement and fundamental analysis on macroeconomic forecasts by assessing the explanatory power of the F-Score. The F-Score assesses three areas of a company's financial position:

profitability, financial liquidity/leverage and operational efficiency. Detailed descriptions about the composition of the F-Score are provided in the literature review.

Combining fundamental analysis with macroeconomic forecasting is a new field of study. Konchitchki and Patatoukas (2014) abandon the idea of using aggregate accounting information solely on the firm level but attempt to make use of macroeconomic predictive characteristics of aggregated financial statement analysis of influential firms. Moreover, this idea fills a void in the literature in terms of evaluating SPF forecast errors. While much prior literature deals with improvements related to econometric models (Bratu, 2012; Croushore, 2010), the concept of Konchitchki and Patatoukas (2014) considers the heretofore disregarded usefulness of aggregate accounting data. Also, Kalay, Nallareddy & Sadka (2018) pick up on their research, to demonstrate the explaining power of firm-level shocks on macroeconomic shocks. The intention of this study is to further widen the perspective and assess the predictive power of fundamental analysis, proxied by the F-Score, on macroeconomic forecasts.

In the following subsection the evolution of the usefulness of financial statement data is discussed. Section 3 addresses the utilised data sources and applied methodology. Section 4 presents the results of the proposed models, including statistical interpretation and economical intuition. Section 5 concludes the study by addressing the main findings and acknowledging about limitations of the study and presenting concerns for future research.

2. Literature Review

2.1 Evolution of the Utilisation of Accounting Earnings Data

Konchitchki and Patatoukas (2014) shift the focus of the predictive power of financial statement analysis from the micro to the macro level. Therefore, the following section serves as quick orientation of the evolution of financial statement analysis and the use of its predictive power.

In the late 1980s, Ou and Penman (1989) propose a strategy for yielding abnormal returns based on financial statement analysis. The basic idea is to invest in firms that show strong

fundamentals and thus benefit from imperfect financial markets, as these fundamental measures are not fully incorporated in current stock prices, which leads to the undervaluation (overvaluation) of equity values with strong (weak) fundamentals. This discovery can be considered as first indicator that accounting data contain leading information for subsequent periods and thus be the starting point for this study. This research is further refined by Abarbanell and Bushee (1998) by considering the grouped variables in isolation and adding causal reasoning to the statistical relationships. The methodology is developed even further when Soliman (2008) researches the persistence of financial ratios by utilising the so-called DuPont analysis which decomposes return on net operating assets (RNOA), into the two-profitability driver asset turnover (ATO) and profit margin (PM). Decomposed into the DuPont profitability ratio, the variables demonstrate persistence and therefore the potential to possess predictive power for subsequent periods. Lately, the American Accounting Association has built up on research conducted by Dechow (1994) who demonstrates that accrual earnings are more advanced for measuring firm performance in the short term than actual cash flows, suggesting that accounting earnings data possess much better predictive power for subsequent cash flows than cash flows of the current period (Moehrle et al., 2009). By following the wide-spread assumption that firm value is equal to the present value of companies' future cash-flows (Berk & DeMarzo, 2014), the use of accounting data can lead improvements for firm valuation and economic projections in general. Following these mostly incremental changes in the utilisation of accounting earnings data Konchitchki and Patatoukas (2014) introduce a game changing idea that utilises the predictive power of aggregate accounting data on the macro instead of micro level. The academics focus on the 100 most influential firms ranked by market capitalisation in the US, which are responsible for about 80% of the country's economic activity and therefore provide a reasonable and cost-effective method to proxy the real economy. Their results show that aggregate accounting data contain predictive power for macroeconomic projections and professional forecasters partially

revise their projections of real economic activity according to recently published aggregate accounting data. However, they are not as fully attuned to aggregate accounting data as to stock market data leaving room for improvement. As the classic DuPont breakdown, as well as further refinements of this breakdown are the focus of the latest literature stream and serve as the foundation for this study, they are explained in detail in the following section.

2.2 *Breakdowns*

In the backbone paper of this study, Konchitchki and Patatoukas (2014) assess firm performance by measuring RNOA and decomposing it into the DuPont profitability ratio which is composed of two parts: ATO, measured by volume of sales over net operating assets and PM, which is calculated by operating income after depreciation over volume of sales. The former measures firms' asset utilisation, or how efficiently assets are used to generate sales and consequently the extent to which firms are able to materialise on their assets. The latter measures firms' operating efficiency by revealing how much money firms generate per dollar of sales and their ability to control costs and charge premium prices (Fairfield & Yohn, 2001). Thus, the DuPont profitability ratio provides insights about the drivers of firms' operating profitability and demonstrates firms' value creation potential, as it is based on unlevered financial statements and unbiased by any financing decisions (Baumann, 2014). They find that RNOA is a significant predictor for subsequent GDP growth, which is mainly driven by the predictive power of PM.

Ivanov (2016) argues that the classic DuPont breakdown does not represent the optimal breakdown for the purpose of macroeconomic forecasting. Thus, he introduces the alternative DuPont breakdown, which incorporates the effect of financial leverage:

$$ROE = ROBA + \underbrace{(ROBA - \text{After tax Cost of Debt})}_{\text{Spread}} \times \text{Financial Leverage}$$

The central difference to the classic DuPont breakdown is that ROE, rather than RNOA, is decomposed. Return on business assets (ROBA) measures the profitability from the company's

operating and investment activities. The spread is calculated as the difference between ROBA and the after-tax cost of debt. It infers the crucial importance that a company earns more than the invested funds cost as otherwise, the company destructs, rather than creates value for both shareholder and debtholder. Hence, if firms manage to earn a higher return than their cost of debt, they have the potential to grow, which in turn can be an indicator for macroeconomic growth. Ivanov (2016) finds that the spread component is a powerful predictor for subsequent macroeconomic activity and thus proves that a levered perspective on firm performance provides valuable information for macroeconomic forecasting.

F-Score (Total_FScore)

As this study attempts to further simplify the methodology, the F-Score is utilised to benefit from its easily understandable binary nature. The F-Score is a financial performance metric that aims to assess firms' fundamentals according to nine binary financial performance signals. It is first introduced by Piotroski in 2000, who attempts to assess firms' financial health to foresee price-adjusting effects. Consequently, firms with weak (strong) fundamentals are on average overvalued (undervalued). Thus, investors can earn abnormal profits by investing (divesting) in undervalued (overvalued) stocks and hence exploiting market inefficiencies (Piotroski, 2000; Piotroski & So, 2012). However, the proposed simplicity comes at a cost. Relevant factors may not be considered in the assessment due to its binary nature which can lead to biased outcomes. Nevertheless, Piotroski (2000) and Piotroski and So (2012), show that the F-Score leads to significant results and implications for firms' current financial positions and contains information about firm's next period's financial strength. To test the extent to which quarterly aggregate changes in Total F-Scores provide insights for forecasting, the first hypothesis is proposed:

Hypothesis 1: Quarterly aggregate changes in Total F-Scores contain predictive power for subsequent macroeconomic growth.

The composition of the F-Score can be grouped into three so-called Partial F-Scores, which are assigned to the following areas: profitability, liquidity/leverage and operational efficiency. Hence, the second hypothesis refers to the overall predictive power of the three Partial F-Scores:

Hypothesis 2: Quarterly aggregate changes in Partial F-Scores contain predictive power for subsequent macroeconomic growth.

Current profitability and cash collection provide information about a company's ability to generate funds internally. Any enterprise experiencing a positive cash flow or earning profits can demonstrate that it is capable of generating funds from operating activities. Moreover, increasing earnings is an accurate predictor of a company's future ability to generate positive cash flows. However, earnings that are primarily driven by positive accrual accounting adjustments are a bad signal for future profitability. Having excessive positive accrual accounting adjustments indicates that earnings exceed cash flow from operations (CFO), this is in turn, an indicator that the company is unable to collect cash and realise its returns. (Piotroski, 2000; Sloan, 1996). Piotroski (2000) defines four variables in order to assess firms' profitability: ROA (BS1_ROA), change in ROA (BS2_ΔROA), CFO (BS3_CFO) and current year's net income before extraordinary items less CFO (BS4_Accrual). The predictive power of the profitability Partial F-Score is consequently tested, which leads to the following hypothesis:

Hypothesis 2.1: Quarterly aggregate changes in the profitability Partial F-Scores show power for subsequent macroeconomic growth

The second area of financial performance signals refers to a company's ability to meet future (debt service) obligations. Piotroski (2000) assumes that an increase in leverage, a lack of current assets and the reliance on external funding are signals for weak financial fundamentals. Therefore, he introduces three variables related to debt obligations and liquidity issues: Change in a firm's long-term debt levels (BS5_Debt), change in a firm's current ratio (BS6_currentratio), Equity Issuance (BS7_Equity). Overall, the liquidity and leverage Partial F-Score indicates a firm's ability to yield

a higher return than the used cost of capital and thus provides insights into the well-being of a company, since a successful and sustainable firm does not only rely on overall profitability but is also required to pay back its debtholders (Piotroski, 2000). Therefore, whether the predictive power of financial liquidity/ on macroeconomic forecasts is investigated:

Hypothesis 2.2: Quarterly aggregate changes in the liquidity and leverage Partial F-Score show predictive power for subsequent macroeconomic growth.

As final area for firms' financial health, operational efficiency is assessed. Therefore, the two components of the classic DuPont breakdown, the decomposition of ROA into ATO (BS8_ATO) and PM (BS9_PM), are tested for their implications for macroeconomic forecasting:

Hypothesis 2.3: Quarterly aggregate changes in the operational efficiency Partial F-Score show predictive power for subsequent macroeconomic growth.

2.4 The Stock Market as Benchmark Model for publicly available Information

Macroeconomic predictions based on aggregate accounting data are only relevant for future research if they do not overlap with information that is already used by the public. Therefore, an easily available benchmark model must be chosen to examine whether variables demonstrate incrementally useful value in addition to information that is already captured by the market. According to the efficient market hypothesis, the stock market reflects timely information about the current well-being and consequently also about the future outlook of the economy. Consequently, the stock market can be considered as leading indicator for future changes in macroeconomic growth. (Fama, 1990; Fama & French, 1992). The most famous and broad-based stock market index for the US economy is the S&P 500 index, it includes the most valuable companies in the United States which are listed on the NYSE or NASDAQ stock market exchanges. The S&P 500 differs from other popular US stock indexes, such as the Dow Jones Industrial Average or the NASDAQ composite index, as the incorporated companies are much more diverse and therefore provide a useful solution to proxy the entire economy (Berk &

DeMarzo,2014). Consequently, fluctuations do not depend excessively on distinct industries but reflect a broad-based set of companies from various areas and hence serves as a good proxy for the entire US economy. Consequently, it is tested for the extent to which the findings are incrementally useful to information that is already incorporated in the stock market:

Hypothesis 3: Adjusting models for predicting macroeconomic growth (GDP) by adding insights from financial statement analysis adds incremental value and does not coincide with already available information in the market, proxied by the S&P 500 stock market index.

2.5 Proxy for the Real Economy

The key strength of the research design of Konchitchki and Patatoukas (2014) is its simplicity and cost efficiency, because only the 100 most influential firms need to be analysed in order to create a reasonable proxy for the real economy. The top 100 account for roughly 82% of the overall market capitalisation and show that the correlation between aggregate changes in accounting profitability (proxied by Δ RNOA) of the 100 largest firms and all firms is 0.99.

The researchers use firms' market value (MV) to determine their relative size and thus rank the corporations. Using MV as ranking method leads to potential drawbacks. Firstly, stocks are publicly traded and reflect high volatility. Secondly, markets are not as efficient in practice as in theory, so that the ranking can be biased due to market imperfections (Berk & DeMarzo, 2014). Contrarily, utilising MV is reasonable assuming that those stocks receive the most attention from the public and are part of private portfolios and portfolios from institutional investors. Therefore, these companies do have significant impacts on the real economy.

Another approach could be the use of book values (BV). This approach has the advantage that BV are more regulated than MV due to accounting standards that aim to provide comparability and transparency. Moreover, BV are only updated quarterly, while MV show significant volatility on a daily basis. On the other hand, BV can also be biased by differing accounting habits between different companies while still complying with the regulations. Moreover, intangibles are hard to

estimate and usually poorly represented by the BV of a company. Further, assets, particularly property, plants & equipment, that were purchased several years before the reporting date can be biased due to effects of inflation. Consequently, it is hard to define which method is best for determining a ranking that precisely reflects the 100 largest firms. Nevertheless, in this thesis, MV are used to make the study more comparable to the findings of Konchitchki and Patatoukas (2014).

2.6 Survey of Professional Forecasters and macroeconomic forecasting

In 1968, the American Statistical Association (ASA) and the National Bureau of Economic Research (NBER) began conducting research to develop the ASA/NBER Economic Outlook Survey, which is today known as the SPF. At this point of time they sent out surveys to experts in different professions to precisely anticipate future economic trends. Despite changes, the key variables of the study have always referred to output, inflation and interest rate predictions. The surveys are sent anonymously to participating experts to encourage their willingness to participate in the survey (Federal Reserve Bank of Philadelphia, 2018). In 1990 the Federal Reserve Bank of Philadelphia took over the SPF after ASA and NBER showed a lack of interest in continuing to conduct the survey. (Federal Reserve Bank of Philadelphia, 2018). In respect to this study, these macroeconomic forecasts are crucial to further test for the incremental usefulness of the tested variables and investigate if forecasters already incorporate this type of data in their models.

Hypothesis 4: SPF macroeconomic forecasters revise their macroeconomic forecasts according to recently published accounting data, proxied by Piotroski's (2000) Total F-Score or Partial F-Scores.

2.6.1 SPF Criticism

The primary point of criticism of the SPF is its unsatisfying performance during respectively before crisis. One possible explanation is proclaimed by Fildes and Stekler (2002), who argue that macroeconomic forecasters tend to make systematic errors. They underestimate growth during periods of economic expansion and overestimate it in recessions. This systematic behaviour is

highly linked to the overreaction of forecasters during economic downturns and the underreaction during economic booms, which ultimately leads to the conclusion that macroeconomic forecasts demonstrate a smoothing trend compared to the observed variable (Wieland & Wolters, 2011).

The ultimate goal of the SPF is to create accurate projections about the future macroeconomic development and minimise forecast errors. Hence, to test whether forecasters are fully or only partially attuned to the examined aggregate accounting performance metrics, it is investigated whether forecast errors are predictable based on leading information contained in aggregate changes in Partial or Total F-Scores:

Hypothesis 5: SPF macroeconomic forecasters are fully attuned to the predictive power of quarterly aggregate changes in Total and Partial F-Scores.

3. Methodology

3.1 Data Collection

To sufficiently conduct the proposed research, it is necessary to gather data from three different sources. Firstly, accounting data on a quarterly basis are retrieved from Compustat. Data are extracted for each individual company per quarter from the S&P 500 index. Although only the 100 largest companies ranked by MV per quarter are considered for the research, the dataset is further reduced by removing companies containing unavailable data from the sample. To compensate for these companies, the next largest company (according to MV) is added to the dataset. The observed time horizon spans from 1990 Q1 and 2018 Q1. The time span cannot be further expanded as Compustat does not provide data for several key statistics (e.g. operating cash flow and costs of goods sold) prior to 1989. As year-over-year changes are used in order to adjust for the effect of seasonality, the time span is reduced further to begin in 1990. Moreover, quarterly S&P 500 returns are extracted from Compustat as well, to compute 3-, 6-, 9-, 12- and 24-month buy-and-hold returns for every examined period. Secondly, quarterly measures of real GDP and its respective growth rates are retrieved from the Bureau of Economic Analysis. Finally, quarterly

projections from the SPF from the Federal Reserve Bank of Philadelphia are extracted. For the purpose of this study two-and one-period ahead GDP forecasts are relevant.

3.2 *Variable Clarification*

To check for leading aggregate changes in Total and Partial F-Scores the ultimate goal is to compute the quarterly changes in aggregate F-Scores. Therefore, the aggregate averages of the individual companies' binary signals are calculated per quarter. Year-over-year changes are subsequently computed in order to control for the effect of seasonality. In the following, these aggregate changes serve as independent variables. For instance, to compute the profitability Partial F-Score variable ($\Delta Profitability$), the aggregate averages of the four profitability-related binary signals are summed up per quarter and subsequently transformed into aggregate changes by taking the year-over-year changes. The top 100 companies are ranked according to their MV at the end of the quarter. To test whether macroeconomic forecasters utilise recently published financial statements data in their macroeconomic projections, it is tested whether they adjust their forecasts according to the newly available data. Therefore, the difference between GDP forecasts at quarter_{t-1} and quarter_{t-2} is constructed as a dependent variable. Furthermore, a dependent variable is constructed that indicates forecast errors (projected minus actual value), which aims to clarify whether forecasters fully consider aggregate accounting data in their projections.

3.3 *Models*

To check for the proposed hypotheses, all models and their respective tables have been calculated and created with the statistical software packages of Microsoft Excel and Stata. The following subsection introduces the proposed models, which aim to validate or reject the hypotheses.

Model 1 tests for the predictive power of Total F-Scores as proposed in Hypothesis 1:

$$g_{q+1} = \alpha + \beta_1 \times \Delta Aggregate\ Total\ FScore_q + \varepsilon_{q+1} \quad (1)$$

If equation (1) does not yield significant results the partial F-Scores: profitability, leverage/liquidity and operational efficiency are tested for significant predictive power for real GDP

growth. If equation (1) does show a significant relationship to real GDP growth, Hypotheses 2 to 2.3 are tested to determine which of the Partial F-Scores most impact this relationship:

$$g_{q+1} = \alpha + \sum \beta_k \times \Delta \text{Aggregate Partial FScores}_q^k + \varepsilon_{q+1} \quad (2)$$

To further investigate the individual driver for a significant relationship between Partial F-Scores and subsequent GDP growth the binary signals are tested for their individual predictive power.

$$g_{q+1} = \alpha + \sum \beta_k \Delta \text{Aggregate Individual Binary Signal}_q^k + \varepsilon_{q+1} \quad (3)$$

To check for incremental value for macroeconomic forecasting, it is tested whether adding the previously tested aggregate accounting data to a model that predicts subsequent GDP growth by stock market returns improves the quality of the model. To use a strong variable to predict real GDP growth by stock market data, different time periods are assessed. The timespan with the strongest explanatory power is used as basis to check for the incremental value of aggregate accounting data and test the third hypothesis.

$$g_{q+1} = \alpha + \gamma * \text{stockmarket return}_{t-k \rightarrow t} + \sum \beta_k \times \Delta \text{Aggregate Total FScore}_q^k + \varepsilon_{q+1} \quad (4)$$

In case Model (4), or a modification (e.g., testing for Partial F-Scores or individual binary signals), yields an improvement in terms of model fit, it is further tested whether macroeconomic forecasters incorporate this type of data and revise their forecasts after recently available financial statement data have been published. Therefore, Hypothesis 4 is tested through forecast revisions, meaning the difference between the two- and one-period-ahead forecasts can be explained by the information contained in newly available financial statement data associated with Total and Partial F-Scores as well as the binary signals.

$$E_q[g_{q+1}] - E_{q-1}[g_{q+1}] = \alpha + \gamma * \text{stockmarket return}_{t-k \rightarrow t} + \sum \beta_k \times \Delta \text{Aggregate Total/Partial FScore}_q^k + \varepsilon_{q+1} \quad (5)$$

Nonetheless, this does not necessarily explain the extent to which professionals make use of these explanatory variables. Thus, forecast errors are further investigated. If aggregate changes in Total F-Scores and Partial F-Scores show significant predictive power to project forecast errors, this

reveals that macroeconomic forecasters are not fully attuned to this type of leading information and real GDP growth projections could be improved in an economically significant manner.

$$g_{q+1} - E_q[g_{q+1}] = \alpha + \gamma * stockmarket\ return_{t-k \rightarrow t} + \Sigma \beta_k \times \Delta Aggregate\ Total / Partial FScore_q^k + \varepsilon_{q+1} \quad (6)$$

4. Results and Discussion

The conducted statistical analysis provides mixed inferences for the proposed hypotheses with the consequence that the interpretation of the results requires further guidance and alternative explanations must be discussed. Hence, the results and the interpretation of the results are presented together. The subsequent sections reintroduce the models, evaluates the proposed hypotheses, presents the result and interprets the findings in an economical context.

4.1 Descriptive Statistics

The descriptive statistics of the analysed variables are measured at the end of each calendar quarter; thus, their timeliness depends on the respective reporting date of the individual companies. Table 7 displays summary statistics of the key variables. The dependent variable of greatest concern, real GDP growth (ΔGDP), fluctuates between -1.86% and 2.45% with a mean of 1.11% and a standard deviation of 0.63%. The Partial F-Scores show the following fluctuations: Profitability ($\Delta Profitability$) fluctuates around a mean of 0.47% with a standard deviation of 4.5%, liquidity/ leverage (ΔLiq_Lev) shows a mean of 0.62% with a standard deviation of 8.99% and operational efficiency ($\Delta Operational_Eff$) fluctuates around a mean of 0.46% with a standard deviation of 8.65%. The summary statistics of the Total F-Score ($\Delta Total_FScore$) is less volatile due to the influence of all three partial F-Scores which balance the individual effects.

Table 8 displays pairwise correlations and provides first tendencies about the respective predictive power of the variables. It depicts that the model does not suffer from multicollinearity, as the three Partial F-Scores do not show significant correlation with each other. Additionally, a variance

inflation factor analysis is performed and confirms the results of no multicollinearity. Moreover, all three Partial F-Scores show significant and strong correlation with the Total F-Score, which is logical, since on the individual firm level, Total F-Scores are the sum of Partial F-Scores. Furthermore, the table indicates a weakly significant correlation of the Partial F-Score of liquidity and leverage with GDP growth and a highly significant correlation with forecast errors.

4.2 *Predictive Power of Aggregate Changes in Total and Partial F-Scores*

Throughout the study, several time series regressions are presented. The models are compared by the goodness-of-fit measure adjusted R-squared (R^2), as it indicates the extent to which the dependent variable is predictable from the independent variable(s) and penalises for the inclusion of redundant variables (Sharpe, DeVeaux & Velleman, 2012). Moreover, the models are estimated by ordinary least squares regressions, and the statistical inferences are based on Newey and West's (1987) standard errors and two-sided p-values. All of the explanatory variables withstand the robustness tests for up to four lags. As robustness tests, an augmented Dickey Fuller test and additionally a Dickey-Fuller-General Least Squares test are used. Newey and West's (1987) standard errors possess the advantage of being robust to autocorrelation and heteroscedasticity; however, this comes at the cost of putting more pressure on the significance of variables.

To begin, Table 1 refers to the predictive power of aggregate Total F-Scores, as well as Partial F-Scores on subsequent GDP growth. Aggregate changes in Total F-Scores do not appear to be a significant predictor of GDP growth. The coefficient of 0.02 is not significant at the 90% confidence level but indicates a p-value of 0.167. Consequently, Hypothesis 1 is rejected, as the tests establish, at best, very weakly significant predictive content within aggregate changes in Total F-Scores. At first, this finding is surprising, as the Total F-Score is a sound estimator for firm's fundamental strength on the micro-level. From the results, three potential and not mutually exclusive, conclusions can be drawn. First, aggregate changes in Total F-Scores are only relevant and meaningful on the micro-level as indicated by Piotroski (2000). Second, aggregate changes

in Total F-Scores are only partially meaningful, and hence potentially meaningful results are cancelled out by other insignificant factors. Third, the considered key metrics are meaningful and contain leading information to predict subsequent macroeconomic activity, but due to the transformation into binary signals, much information is lost, and the predictive power is reduced.

To determine whether the F-Score in general does not entail predictive power or whether various factors within the components cancel each other out, the three partial F-Scores are analysed: In Model 2 to 2.4, it becomes obvious that the Partial F-Scores representing profitability and operational efficiency are very weak variables and do not incorporate predictive power for subsequent real GDP growth. Conversely, the Partial F-Scores representing liquidity and leverage do show significant results for macroeconomic projections. With two highly insignificant variables in Model 2 the goodness-of-fit measure adjusted- R^2 even becomes negative, which further highlights their redundancy. Using the Partial F-Score of liquidity and leverage in isolation (Model 2.2), the predictive content remains significant at the 95% confidence level, and a coefficient of 0.0109. As a matter of fact, a one percent aggregate increase in this variable is associated with a 0.0109 % increase in real GDP growth in the subsequent quarter. The results are related to the previously obtained pairwise correlations that do not show significant correlation for the two insignificant Partial F-Scores with subsequent GDP, but, indicate a positive correlation for the $\Delta\text{Liq_Lev}$ variable which is close to be significant at the 90% confidence level. Although the adjusted- R^2 improves in comparison to the previous model that includes all three Partial F-Scores, the quality of the model remains relatively weak, as the included variable only accounts for 1.45% of the total variation of the dependent variable. Therefore, Hypothesis 2.1 and 2.3 are rejected, while Hypothesis 2.2 is supported by the results.

To further investigate the results, the liquidity/leverage variable is decomposed into its three binary signals to determine precisely what exactly causes the variable to be a significant predictor. Regarding Table 2 it is striking that neither grouped nor in isolation do the three binary signals

indicate predictive power for subsequent real GDP growth. The negative adjusted- R^2 stresses further the poor predictive ability of the explanatory variables. Thus, it appears likely that in combination the liquidity/leverage variable is an accurate indicator for measuring individual firm fundamentals, as advertised by Piotroski (2000). Hence, it becomes obvious that the set of variables needs to be chosen carefully, as only when they are bundled as a grouped variable, the predictive content becomes significant. Considering the operational efficiency Partial F-Score, the insignificant results seem to be caused by two complementary effects. Firstly, while Konchitchki and Patatoukas (2014) report that PM is a leading indicator for subsequent GDP growth, the results of this study establish no significant predictive power, thus, it is obvious that a substantial amount of information is lost during the transformation into the binary signals. Secondly, the chosen set of variables for the profitability Partial F-Score is inappropriate to demonstrate predictive power on the macro level. Konchitchki and Patatoukas (2014) indicate that ATO does not contain predictive power to forecast subsequent macroeconomic growth. Consequently, the two binary signals that comprise to the operational efficiency Partial F-Score do not complement each other. One reason why ATO and thus operational efficiency are not a leading indicator for subsequent GDP growth are their lagged effects on firm performance. Improvements in operational efficiency do not cause an immediate effect but instead respond with a lag of several periods. As a consequence, the variable does not contain predictive power for subsequent GDP growth. The same reasoning holds for the profitability Partial F-Score, except that profitability related improvements tend to show a sooner effect on firm performance. (Baik et al., 2013)

4.4 Incremental Predictive Power of Aggregate Changes in Total and Partial F-Scores

The collection and analysis of aggregate accounting data incurs non-trivial costs, while stock market data are easily accessible and do not impose any costs on macroeconomic forecasters. Hence, from a practical perspective, the analysis of aggregate accounting data can only be relevant in terms of its incremental predictive power compared to stock market returns data. Table 6

suggests that one-year stock market returns provide the most powerful model to foresee subsequent macroeconomic activity and are hence used as benchmark model. These findings are in line with the research from Konchitchki and Patatoukas (2014).

Table 3 shows the respective results of Total F-Score (Model 4.1) as well as the liquidity and leverage Partial F-Score (Model 4.2) as explanatory variables. Model 7.4 indicates, as expected, that the one-year stock market return variable is a significant predictor for macroeconomic activity. The adjusted- R^2 is increased in comparison to Model 7.4 which only considers one-year stock market returns as single explanatory variable. The goodness-of-fit measure increases from 20.77 % to 21.67 %. Hence, aggregate changes in Total F-Scores seem to indeed contain incrementally useful information to predict subsequent macroeconomic activity. However, it needs to be noted that the model only improves slightly and the contribution of the Total F-Score is, at best, weakly significant so that any conclusions should be drawn carefully.

Similar observations can be made when considering Model 4.2, which includes the liquidity and leverage Partial F-Score and one-year stock market returns as explanatory variables. The stock market return variable is, again, significant, while the Partial F-Score is just like the Total F-Score at best weakly significant as with a p-value of 0.15 it is not significant at the 90% confidence level. The quality of the model, measured by the adjusted- R^2 , improves slightly from 20.77% to 21.37%. Again, these findings need to be considered carefully as the added variable that is supposed to cause the model improvement is, at best, weakly significant. Nevertheless, as the model fit improves, it is assumed that aggregate changes in Total and Partial F-Score can have a positive impact on macroeconomic forecasting, although this impact is minor.

4.5 The use of aggregate changes in Total and Partial F-Scores by macro forecasters

In Table 4 macroeconomic forecast revisions are chosen as dependent variable to investigate if the professional forecasters adjust their projections according to newly available financial statement data and consequently newly available changes in aggregate Total and Partial F-Scores.

The findings in Model 5.1 depict, as expected, significant results for the stock market returns variable at the 99% confidence level, with a positive coefficient of 0.0221. The Total F-Score coefficient indicates a positive coefficient of 0.0201 as well. However, the coefficient comes with, at best, a weak statistical significance and a p-value of 0.153 and thus insignificant at the 90% confidence level. Nevertheless, the quality of the model appears to have improved, as the adjusted- R^2 increases from 16.34% to 16.53% when stock market data are used in isolation to predict forecast revisions from professional forecasters. Hence, it can be concluded that macroeconomic forecasters are aware of some powerful information within aggregate Total F-Scores. However, as the F-Score variable in Model 5.1 demonstrates, at best, a weak statistical significance, conclusions should only be drawn with special considerations. The liquidity/leverage Partial F-Score variable does not contain explanatory power forecast revisions. Thus, professional forecasters do not seem to be aware of the incremental predictive power of this variable on subsequent GDP growth. Consequently, the fourth hypothesis is rejected from the findings.

Another interesting observation that aligns with the findings of Konchitchki and Patatoukas (2014) is that the intercepts of the discussed models are all significantly negative, revealing that macroeconomic forecasters tend to revise their macroeconomic projections downwards as the release date for the BEA NIPA report approaches. These findings are further evidence for the so-called ‘walk-down’ phenomenon, associated with micro-level accounting research, which states that an analyst’s optimism decreases as earnings reporting dates approach (Bamber, Barron, & Stevens, 2011; Barron, Byard, Kim, 2002; Richardson, Teoh, & Wysocki, 2004).

4.6 Predictability of Forecast Errors on aggregate Changes in Total and Partial F-Scores

To examine whether forecasters are fully attuned to the examined variables and whether they can help to minimise forecast errors, time series regressions on subsequent forecast errors with aggregate changes in Total and Partial F-Scores and stock market returns data are conducted.

As weak statistical predictive power for forecast revisions in Total F-Scores is found, no predictive power for subsequent forecast errors is expected. If macroeconomic forecasters are aware of the predictive power of the variables and indeed utilise this information, the variables would not sufficiently explain forecast errors, as the information would have already been included in projections about subsequent macroeconomic activity. Consequently, the Total F-Score variable is expected to contain no predictive power for subsequent forecast errors made by professional forecasters. By assuming that the weak statistical significance of aggregate changes in Total F-Scores for subsequent GDP growth and forecast revisions are valid, the results establish that professionals consistently utilise information contained in aggregate changes of Total F-Score. Moreover, as this study does not identify any predictive power of the liquidity/leverage Partial F-Score variable on subsequent forecast revisions, significant predictive power of this variable on forecast errors made by forecasters would suggest that professionals miss out on the predictive power of aggregate changes in the liquidity/leverage Partial F-Score.

Regarding the examination of aggregate changes in Total F-Scores in isolation from stock market returns data, no significant predictive power for subsequent forecast errors can be observed. With a relatively high p-value of 0.198 and a very weak explanatory power for the total variation of the dependent variable (adjusted- R^2 0.87%), the results suggest either that forecasters are already fully attuned to the leading information of aggregate changes in Total F-Scores or that aggregate changes in Total F-Scores lack predictive power to explain GDP growth and thus forecast errors or a combination of both. However, an, at best, statistically weak relationship between forecast revisions and aggregate changes in Total F-Scores exists. By assuming that the weak statistical predictive power of aggregate changes in Total F-Score on subsequent GDP growth is valid, the results suggest that forecasters consistently utilise information included in this variable. Hence, it is possible that professionals incorporate information about fundamental analysis in general,

which is correlated with aggregate changes in Total F-Scores despite potential information outflow due to their binary nature.

Model 6.2 considers the liquidity/leverage Partial F-Score variable as single explanatory variable, the coefficient of 0.0397 is positive and significant at the 99% confidence level. Moreover, the adjusted- R^2 increases greatly in comparison to Model 6.1 to 10.15%. Thus, aggregate changes in the liquidity/leverage Partial F-Score explain 10.15% of the total variation of subsequent forecast errors. These findings support the identified predictive power of the liquidity/leverage Partial F-Score and reveal that forecasters do not integrate this information in their projections.

Moreover, stock market returns data are considered as single explanatory variable for subsequent forecast errors. The findings do not align with Konchitchki and Patatoukas (2014), who find no predictive power of stock market returns data on forecast errors. Several factors may explain these contradictory findings. First, different time frames are considered; thus, circumstances and the behaviour of macroeconomic forecasters, could have changed. Second, the contradictory findings may result from forecasters making systematic errors. If this occurs, information that could actually help to predict GDP growth may be excluded or improperly considered. Besides, stock market returns data might include information that forecasters are unaware of, resulting in their failure to fully consider them for projections about subsequent GDP growth. In addition, forecasters may have adjusted their methods according to the findings of Konchitchki and Patatoukas (2014) and have thus shifted their focus to aggregate accounting data and away from relevant information from stock market returns. Nevertheless, this potential shift could only be marginally responsible, as Konchitchki and Patatoukas' (2014) findings were published in 2014 and could thus only affect the tests in a maximum of four of the nearly 30 years of observations. Regarding the incremental usefulness of the liquidity/leverage variable after adding stock market returns data as explanatory variable to the regression, the results suggest that the variable adds incremental value. Both variables remain significant at the 99% confidence level, and the quality

of the model improves substantially, from an adjusted- R^2 of 8.89% for stock market returns data in isolation to 17.39% when considering both variables in the model.

The results fulfil the expectations. In Model 6.3, the liquidity/leverage variable shows a coefficient of 0.0368 meaning that a one percent increase in the liquidity/leverage Partial F-Score is associated with a 0.0368% increase in subsequent forecast errors. By assuming that the incrementally useful and weak statistical predictive power of the variable on subsequent GDP growth is valid, the results establish that forecasters fail to utilise the leading information of this variable. The reason that forecast errors are predictable based on the liquidity/leverage Partial F-Score and not the Total F-Score may also be rooted in the tendency of professionals to consider fundamental analysis in general and thus be more attuned to Total F-Scores than to Partial F-Scores. Compared to Konchitchki and Patatoukas (2014) who establish that macroeconomic forecasters fully impound stock market returns data, this study finds different results, as stock market returns data explains a significant part of subsequent forecast errors.

The findings establish either that forecasters are already fully attuned to aggregate changes in Total F-Scores or that they do not contain predictive power for GDP growth, or a combination of both. Moreover, a significant relationship between forecast errors and aggregate changes of the liquidity/leverage Partial F-Score and stock market returns data is found. Both variables are incrementally useful to predict forecast errors. The magnitudes of the estimated coefficients imply that macroeconomic forecasts can be enhanced significantly. Hence, Hypothesis 5 is rejected.

5. Conclusion

This study is based upon a new stream of literature regarding the use of financial statement analysis and macroeconomic forecasting. By utilising a sample of the top 100 US firms ranked by MV, quarterly data on firm fundamentals, proxied by Total and Partial F-Scores, is aggregated.

The results suggest, at best, that aggregate changes in Total F-Scores have weak predictive power, which fails to be significant at the 85% confidence level. By investigating the three Partial F-

Scores, only the liquidity/leverage Partial F-Score variable proves to contain significant predictive power for subsequent macroeconomic growth. The inclusion of the stock market variable puts pressure on the significance of the liquidity/leverage Partial F-Score, suggesting that a substantial portion of the information is already captured by stock market returns data.

Testing for the predictive power of Partial F-Scores on forecast revisions establishes that professionals do not integrate information on the liquidity/leverage variable into their projections, and, at best, some information that is contained within aggregate changes of Total F-Scores.

As final step the predictive power on subsequent forecast errors is assessed. As this study does not find predictive power of the liquidity/leverage Partial F-Score variable on subsequent forecast revisions, but on subsequent real GDP growth and forecast errors, the results suggest that forecasters miss out on the predictive power of aggregate changes in liquidity/ leverage Partial F-Scores and the potential to improve their projections.

5.1 Limitations

Certainly, the conducted study comes with limitations and needs to be considered with reservations. Firstly, the data set needed to be thinned out due to missing data for individual companies and variables. Roughly about one-fourth of the considered companies had to be eliminated and replaced by the next largest company based on MV in the respective quarter. Some of these unanalysed companies were very influential to the economy.

Secondly, as binary variables were analysed, it is conceivable that the analysed variables over- or underestimate the actual effects. The insignificance of the binary signal representing aggregate changes in PM on subsequent macroeconomic growth, serves as a clear indication that substantial information is lost during the transformation.

Thirdly, Financial statements are, according to GAAP, nominal. Konchitchki (2013) finds inflation-based investment strategies yielding abnormal returns, resulting from investors who

incorrectly estimate the effects of inflation. If this theory proves to be correct and the market does miss the effect of inflation, it has a significant influence on the financials and value of companies.

Finally, the methodology applied in this study differs slightly from the original. Konchitchki and Patatoukas (2014) align fiscal quarters with calendar quarters to create a timely match between the time of publishing accounting data and distributing SPF questionnaires. In this study, calendar quarters are assumed, thus financial statements available until the end of the calendar quarter are considered. This approach reduces the number of firms that must be excluded and captures a more representative sample of the top 100 companies in the US. However, it creates a slight mismatch between released accounting data and the distribution of the SPF questionnaires. Hence, the aggregate accounting data used as explanatory variables were, at best, published one month before the distribution of the questionnaires. This might affect the predictive power of the explanatory variables, as the most recent events are not included in the explanatory variables.

5.2 *Future Research*

Macroeconomic forecasting will never be complete but will continuously be developed and refined. Before Konchitchki and Patatoukas (2014) published their findings, professionals were not aware that aggregate accounting data contain predictive power for macroeconomic growth. The transformation into binary signals should be further studied to assess the impact of the information loss. Moreover, alternative financial metrics should be analysed to assess their usefulness for macroeconomic forecasting and optimise resource allocations in the economy.

As the sample size of 100 firms appears to be sufficiently large to contain predictive power for the entire economy, it is of great interest whether the sample size could further be reduced.

The ambiguous results about the predictive power of stock market returns data on forecast errors, compared to the findings of Konchitchki and Patatoukas (2014), should be further investigated to detect potential biases or shifts in forecasting methodology.

6. References

- Baik, B., Chae, J., Choi, S. & Farber, D. B. (2013). Changes in Operational Efficiency and Firm Performance: A Frontier Analysis Approach. *Contemporary Accounting Research*, 30(3), 996-1026. doi:10.1111/j.1911-3846.2012.01179.x
- Bamber, L. S., Barron, O. E. & Stevens, D. E. (2011). Trading Volume Around Earnings Announcements and Other Financial Reports: Theory, Research Design, Empirical Evidence, and Directions for Future Research. *Contemporary Accounting Research*, 28(2), 431-471. doi:10.1111/j.1911-3846.2010.01061.x
- Barron, O. E., Byard D., & Kim O. (2002). Changes in Analysts' Information around Earnings Announcements. *The Accounting Review*, 77(4), 821-846.
- Baumann, M. P. (2014). Forecasting operating Profitability with DuPont Analysis: Further Evidence. *Review of Accounting and Finance*, 13(2), 191-205.
- Berk J. & DeMarzo P. (2014). *Corporate Finance* (3rd ed.). Harlow: Pearson Education Limited.
- Bratu, M. (2012). Point Forecasts based on the Limits of the Forecast Intervals to improve the SPF Predictions. *Business and Economic Horizons*, 8(2), 1-11.
- Carlin W. & Soskice D. (2015). *Macroeconomics – Institutions, Instability and the Financial System* (3rd ed.). New York, NY: Oxford University Press.
- Croushore, D. (2010). An Evaluation of Inflation Forecasts from Surveys Using Real-Time Data. *The B.E. Journal Macroeconomics*, 10(1), 1935-1960 DOI: 10.2202/1935-1690.1677
- Dechow, P. (1994). Accounting Earnings and Cash Flows as Measures of Firm Performance: The Role of Accounting Accruals. *Journal of Accounting and Economics*, 18(1), 3-42.
- Fairfield, P. M. & Yohn T. L. (2001). Using Asset Turnover and Profit Margin to forecast Changes in Profitability. *Review of Accounting Studies*, 6(4), 371-385.
- Fama, E. F. (1990). Stock Returns, expected Returns, and real Activity. *The Journal of Finance*, 45(4), 1089-1108.
- Fama, E. F., & French, K. R. (1992). The Cross-section of expected Returns. *The Journal of Finance*, 47(2), 427-465.
- Federal Reserve Bank of Philadelphia. (2018, August 29) Survey of Professional Forecasters. Retrieved from <https://www.philadelphiafed.org/research-and-data/real-time-center/survey-of-professional-forecasters/>
- Fildes, R., Stekler, H. (2002). The state of macroeconomic forecasting. *Journal of Macroeconomics*, 24(4), 435-468.
- Ivanov K., (2016). Taking the pulse of the real economy III: Sharpening macro forecasts with the debt point of view. *MaastrichtUniversity School of Business and Economics*.
- Kalay, A., Nallareddy, S. & Sadka.G. (2018). Uncertainty and sectoral shifts: The Interaction between Firm-Level and Aggregate-Level Shocks, and Macroeconomic Activity. *Management Science* 64 (1): 198–214.
- Kieso, D., Weygandt, J. and Warfield, T. (2014). *Intermediate Accounting* (2nd ed.). Hoboken: John Wiley & Sons, Inc.
- Konchitchki, Y. (2013). Accounting and the Macroeconomy: The Case of Aggregate Price-Level Effects on Individual Stocks. *Financial Analysis Journal*, 69(6), 40-54.
- Konchitchki, Y., & Patatoukas, P. N. (2014). Taking the pulse of the real economy using financial statement analysis: Implications for macro forecasting and stock valuation. *The Accounting Review*, 89(2), 669-694.
- Konchitchki, Y., & Patatoukas, P. N. (2014). Accounting Earnings and Gross Domestic Product. *Journal of Accounting and Economics*, 57(1), 76-88.
- Moehrle, S. R., Anderson, K. L. Ayres, F. L., Bolt-Lee, C. E., Debreceeny, R. S., Dugan, M. T. & Plummer, E. (2009). The Impact of Academic Accounting Research on Professional Practice: An Analysis by the AAA Research Impact Task Force. *Accounting Horizons*, 23(4), 411-456.
- Newey, W. K., & West, K. D. (1987). A Simple Positive, Semi-definite, Heteroscedasticity and Autocorrelation consistent Covariance Matrix. *Econometrica*, 55(3), 703-708.
- Ou, J. A., & Penman, S. H. (1989). Financial statement analysis and the Prediction of Stock Returns. *Journal of Accounting and Economics* 11(4), 295-329.
- Palepu, K., Healy, P. and Peek, E. (2016). *Business analysis and valuation* (4th ed.). Andover: Cengage Learning EMEA.
- Piotroski, J. D. (2000). Value Investing: The Use of Historical Financial Statement Information to Separate Winners from Losers. *Journal of Accounting Research Center*, 38(1), 1-41.
- Piotroski, J. D. & So, E. C. (2012). Identifying Expectation Errors in Value/Glamour Strategies: A Fundamental Analysis Approach. *The Review of Financial Studies*, 25(9), 2841-2875.
- Richardson, S., Teoh, S. H. & Wysocki, P.D. (2004). The walk-down to beatable analyst Forecasts: The Role of Equity Issuance and Insider Trading incentives. *Contemporary Accounting Research*, 21(4), 885-924-
- Sharpe, N., DeVeaux, R. D., Velleman, P. (2012). *Business Statistics* (2nd ed.). Boston, MA: Pearson Education Inc.
- Soliman, M. T. (2008). The Use of DuPont Analysis by Market Participants. *The Accounting Review*, 83(3), 823-853.
- Sloan, R. G. (1996). "Do Stock Prices fully reflect Information in Accruals and Cash Flows about Future Earnings?" *The Accounting Review*, 71(3), 289-315.
- Wieland, V., Wolters, M. (2011). The Diversity of Forecasts from Macroeconomic Models of the US Economy. *Economic Theory* 47(2/3), 247-292.

8. Appendix

Table 1: Predictive Content of Aggregate Changes in Total F-Score and Partial F-Scores for Subsequent Real GDP Growth

Dependent variable = ΔGDP_{q+1}					
Model	1	2	2.1	2.2	2.3
Intercept	0.011	0.011	0.111	0.0108	0.111
t-statistic	12.02*	11.78*	11.54*	12.44*	11.82*
p-value	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
$\Delta\text{Total_FScore}$	0.02				
t-statistic	1.39				
p-value	0.167				
$\Delta\text{Profitability}$		0.0036	0.57		
t-statistic		0.28	0.569		
p-value		0.783	0.0078		
$\Delta\text{Liq_Lev}$		0.0104		0.0109	
t-statistic		2.41*		2.35*	
p-value		0.018		0.02	
$\Delta\text{Operational_Eff}$		0.0023			0.003
t-statistic		0.39			0.49
p-value		0.695			0.624
Adjusted R2	0.93%	-0.18%	-0.60%	1.45%	-0.73%
This table reports results from time series regressions of subsequent real GDP growth on our quarterly indices of aggregate changes in Total F-Score and Partial F-Scores. We obtain data from the BEA's quarterly advance NIPA reports. We measure quarterly changes in Total F-Score and Partial F-Scores as year-over-year changes in percent. We construct the aggregate time-series using cross-sectional averages based on the 100 largest U.S. listed firms in terms of market value with accounting data released during the respective calendar quarter. The sample period includes 113 quarters from 1990:Q1 to 2018:Q1					

Table 2: Predictive Content of Aggregate Changes in the partial F-Score
Leverage/Liquidity and the respective Binary Signals for Subsequent Real GDP Growth

Dependent variable = ΔGDP_{q+1}				
Model	3	3.1	3.2	3.3
Intercept	0.0109	0.111	0.0111	0.011
t-statistic	11.46*	12.35*	12.14*	11.19*
p-value	< 0.001	< 0.001	< 0.001	< 0.001
ΔLiq_Lev	< 0.001			
t-statistic				
p-value				
$\Delta BS5$	-0.003	0.0004		
t-statistic	-0.1	0.01		
p-value	0.921	0.989		
$\Delta BS6$	0.0088		0.0061	
t-statistic	1.04		0.69	
p-value	0.231		0.492	
$\Delta BS7$	0.0031			0.0024
t-statistic	0.84			0.65
p-value	0.402			0.517
Adjusted R2	-0.83%	-0.90%	-0.37%	-0.01%
<p>This table reports results from time series regressions of subsequent real GDP growth on our quarterly indices of aggregate changes in Partial F-Scores and Binary Signals. We obtain data from the BEA's quarterly advance NIPA reports. We measure quarterly changes in Partial F-Scores and Binary Signals as year-over-year changes in percent. We construct the aggregate time-series using cross-sectional averages based on the 100 largest U.S. listed firms in terms of market value with accounting data released during the respective calendar quarter. The sample period includes 113 quarters from 1990:Q1 to 2018:Q1</p>				

Table 3: Incremental Predictive Content of Aggregate Changes in Total F-Score and Partial F-Scores and Stock Market Returns for Subsequent Real GDP Growth

Dependent variable = ΔGDP_{q+1}			
Model	4.1	4.2	7.4
Intercept	0.0094	0.0094	0.0095
t-statistic	9.18*	8.94*	8.61*
p-value	< 0.001	< 0.001	< 0.001
$\Delta\text{Total_FScore}$	0.019		
t-statistic	1.55		
p-value	0.125		
$\Delta\text{Liq_Lev}$		0.0081	
t-statistic		1.45	
p-value		0.15	
one_year_ret	0.0179	0.017	0.0181
t-statistic	3.12*	2.91*	2.96*
p-value	0.002	0.004	0.004
Adjusted R2	21.67%	21.37%	20.77%
<p>This table reports results from time series regressions of subsequent real GDP growth on our quarterly indices of aggregate changes in Partial F-Scores and Binary Signals. We obtain data from the BEA's quarterly advance NIPA reports. We measure quarterly changes in Partial F-Scores and Binary Signals as year-over-year changes in percent. We construct the aggregate time-series using cross-sectional averages based on the 100 largest U.S. listed firms in terms of market value with accounting data released during the respective calendar quarter. The Stock market returns are measured over one year. The stock market portfolio is proxied by the S&P 500 index sample period includes 113 quarters from 1990:Q1 to 2018:Q1</p>			

Table 4: Association of Revisions in Expectations about Subsequent Real GDP Growth with Aggregate Changes in Total F-Score and Partial F-Scores and Stock Market Returns

Dependent variable = Forecast Revisions (FR)			
Model	5.1	5.2	5.3
Intercept	-0.0024	-0.0023	-0.0023
t-statistic	-2.86*	-2.81*	-2.72*
p-value	0.005	0.06	0.007
ΔTotal_FScore	0.0201		
t-statistic	1.44		
p-value	0.153		
ΔLiq_Lev		0.0068	
t-statistic		0.87	
p-value		0.388	
one_year_ret	0.0221	0.0281	0.0222
t-statistic	5.48*	5.35*	5.20*
p-value	< 0.001	< 0.001	< 0.001
Adjusted R2	16.53%	16.07%	16.34%
<p>This table reports results from time series regressions of subsequent real GDP growth on our quarterly indices of aggregate changes in Partial F-Scores and Binary Signals. We obtain data from the BEA's quarterly advance NIPA reports. We measure quarterly changes in Partial F-Scores and Binary Signals as year-over-year changes in percent. We construct the aggregate time-series using cross-sectional averages based on the 100 largest U.S. listed firms in terms of market value with accounting data released during the respective calendar quarter. The Stock market returns are measured over one year. The stock market portfolio is proxied by the S&P 500 index sample period includes 113 quarters from 1990:Q1 to 2018:Q1</p>			

Table 5: Predictive Content of Aggregate Changes in Total F-Scores and Partial F-Scores and Stock Market Returns for Subsequent Real GDP Growth Forecast Errors

Dependent variable = Forecast Errors (FE)				
Model	6.1	6.2	6.3	6.4
Intercept	0.0007	0.0006	-0.001	-0.001
t-statistic	0.46	0.42	-0.74	-0.66
p-value	0.644	0.677	0.461	0.513
ΔTotal_FScore	0.0336			
t-statistic	1.29			
p-value	0.198			
ΔLiq_Lev		0.0397	0.0368	
t-statistic		3.95*	4.40*	
p-value		< 0.001	< 0.001	
one_year_ret			0.0185	0.0202
t-statistic			3.38*	3.89*
p-value			0.001	< 0.001
Adjusted R2	0.87%	10.15%	17.39%	8.69%
<p>This table reports results from time series regressions of subsequent real GDP growth forecast errors on our quarterly indices of aggregate changes in Partial F-Scores and Binary Signals and stock market returns. We measure subsequent real GDP growth forecast errors as the difference between subsequent real GDP growth and the corresponding mean consensus forecast as of quarter q from the SPF. We obtain data from the BEA's quarterly advance NIPA reports. We obtain the SPF mean consensus forecasts of real GDP growth from the Federal Reserve Bank of Philadelphia. We measure quarterly changes in Partial F-Scores and Binary Signals as year-over-year changes in percent. We construct the aggregate time-series using cross-sectional averages based on the 100 largest U.S. listed firms in terms of market value with accounting data released during the respective calendar quarter. The Stock market returns are measured over one year. The stock market portfolio is proxied by the S&P 500 index sample period includes 113 quarters from 1990:Q1 to 2018:Q1</p>				

Table 6: Predictive Content of Stock Market Returns (Proxy: S&P 500) for Subsequent
Real GDP Growth

Dependent variable = ΔGDP_{q+1}					
Model	7.1	7.2	7.3	7.4	7.5
Intercept	0.106	0.0101	0.0098	0.0095	0.0095
t-statistic	10.34*	10.03*	9.42*	8.61*	7.06*
p-value	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
three_mon_ret	0.2433				
t-statistic	1.84				
p-value	0.069				
six_mon_ret		0.0237			
t-statistic		2.66*			
p-value		0.009			
nine_mon_ret			0.2067		
t-statistic			2.93*		
p-value			0.004		
one_year_ret				0.0181	
t-statistic				2.96*	
p-value				0.004	
two_year_ret					0.0082
t-statistic					2.33*
p-value					0.022
Adjusted R2	7.46%	15.95%	19.35%	20.77%	10.53%
<p>This table reports results from time series regressions of subsequent real GDP growth on buy-and-hold stock market returns. Stock market returns are measured over 3-, 6-, 9-, 12- & 24-month periods. We obtain data on real GDP growth from BEA's quarterly advance NIPA reports. The S&P 500 index is used as proxy for the stock market portfolio. The sample period includes 113 quarters from 1990:Q1 to 2018:Q1</p>					

Table 7: Descriptive Statistics

Variable	Observations	Mean	Std. Dev.	Min	Max
ΔBS5 Debt	113	0.0155305	0.215987	-0.4098361	0.6153846
ΔBS6 currentratio	113	0.0035251	0.0753372	-0.2289157	0.1774194
ΔBS7_Equity	113	0.0425513	0.2445081	-0.5555556	0.88
ΔProfitability	113	0.0047196	0.044988	-0.1094675	0.1495017
ΔLiq_ Lev	113	0.0062246	0.0898885	-0.1823575	0.3167702
ΔOperational Eff	113	0.004638	0.086505	-0.1617647	0.2181818
ΔTotal_Fscore	113	0.0036866	0.0424686	-0.0931677	0.1258741
ΔGDP	113	0.011106	0.0063972	-0.0185804	0.0244752
three mon ret	113	0.0208491	0.0756999	-0.2255822	0.2086705
six mon ret	113	0.0426382	0.1102373	-0.3159316	0.3248775
nine mon ret	113	0.0653752	0.1386276	-0.3766641	0.3975961
one year ret	113	0.0890873	0.1640707	-0.3967869	0.4656899
two year ret	113	0.1905303	0.2614663	-0.4384598	0.7068164
F Revision	113	-0.0003121	0.0087966	-0.0294212	0.0324935
F Error	113	0.0008348	0.0107808	-0.0261803	0.0382249

Table 8: Pairwise Correlations

	ΔProfitability	ΔLiq_ Lev	ΔOperational Efficiency	ΔTotal F-Score	ΔOne_year_ret	ΔForecast Revision	ΔForecast Error	ΔGDP
ΔProfitability	1.0000							
ΔLiq_ Lev	0.1810* 0.0550	1.0000						
ΔOperational Efficiency	0.0946 0.3191	0.0560 0.5558	1.0000					
ΔTotal F-Score	0.06929* 0.0000	0.7152* 0.0000	0.4846* 0.0000	1.0000				
ΔOne_year_ret	-0.1538 0.1039	0.0847 0.3724	0.1114 0.2399	0.0188 0.8431	1.0000			
ΔForecast Revision	0.0532 0.5757	0.1042 0.2722	0.0307 0.7470	0.1047 0.2696	0.4133* 0.0000	1.0000		
ΔForecast Error	-0.1642* 0.0822	0.3309* 0.0003	0.0713 0.4528	0.1325 0.1619	0.3083* 0.0009	0.1189 0.2099	1.0000	
ΔGDP	0.0548 0.5640	0.1527 0.1063	0.0410 0.6661	0.1348 0.1546	0.4634* 0.0000	0.2958* 0.0015	0.1856* 0.0491	1.0000

*significance at the 90% confidence level

Table 9:

Regression of $g_{q+1} = \alpha + \beta_1 \times \Delta \text{Aggregate Total FScore}_q + \varepsilon_{q+1}$

Regression with Newey-West standard errors Number of obs = 113
maximum lag: 4 F(1, 111) = 1.93
Prob > F = 0.1671

ΔGDP	Newey-West		t	P> t	[95% Conf. Interval]	
	Coef.	Std. Err.				
$\Delta \text{Total_FScore}$.0203045	.0146001	1.39	0.167	-.0086265	.0492355
_cons	.0110311	.000918	12.02	0.000	.0092121	.0128502

Table 10:

Regression of $g_{q+1} = \alpha + \Sigma \beta_k \times \Delta \text{Aggregate Partial FScores}_q^k + \varepsilon_{q+1}$

Regression with Newey-West standard errors Number of obs = 113
maximum lag: 4 F(3, 109) = 1.95
Prob > F = 0.1260

ΔGDP	Newey-West		t	P> t	[95% Conf. Interval]	
	Coef.	Std. Err.				
$\Delta \text{Profitabil~y}$.00362	.013094	0.28	0.783	-.0223319	.0295718
$\Delta \text{Liq_Lev}$.0104209	.0043308	2.41	0.018	.0018374	.0190044
$\Delta \text{Operationa~f}$.0022495	.0057254	0.39	0.695	-.009098	.013597
_cons	.0110136	.0009353	11.78	0.000	.0091599	.0128673

Table 11:

Regression of $g_{q+1} = \alpha + \beta_1 \Delta \text{Aggregate Profitability Partial FScore}_q + \varepsilon_{q+1}$

Regression with Newey-West standard errors Number of obs = 113
maximum lag: 4 F(1, 111) = 0.33
Prob > F = 0.5695

ΔGDP	Newey-West		t	P> t	[95% Conf. Interval]	
	Coef.	Std. Err.				
$\Delta \text{Profitabil~y}$.0077981	.0136676	0.57	0.569	-.0192851	.0348813
_cons	.0110692	.000959	11.54	0.000	.0091689	.0129694

Table 12:

Regression of $g_{q+1} = \alpha + \times \beta_1 \Delta \text{Aggregate Liquidity_Leverage Partial FScore}_q + \varepsilon_{q+1}$

Regression with Newey-West standard errors Number of obs = 113
maximum lag: 4 F(1, 111) = 5.54
Prob > F = 0.0204

Δ GDP	Newey-West		t	P> t	[95% Conf. Interval]	
	Coef.	Std. Err.				
Δ Liq_Lev	.0108701	.0046197	2.35	0.020	.0017159	.0200243
_cons	.0110383	.0008871	12.44	0.000	.0092804	.0127963

Table 13:

Regression of $g_{q+1} = \alpha + \times \beta_1 \Delta \text{Aggregate Operational Efficiency Partial FScore}_q + \varepsilon_{q+1}$

Regression with Newey-West standard errors Number of obs = 113
maximum lag: 4 F(1, 111) = 0.24
Prob > F = 0.6244

Δ GDP	Newey-West		t	P> t	[95% Conf. Interval]	
	Coef.	Std. Err.				
Δ Operationa~f	.0030339	.0061799	0.49	0.624	-.009212	.0152799
_cons	.0110919	.0009383	11.82	0.000	.0092325	.0129513

Table 14:

Regression of $g_{q+1} = \alpha + \Sigma \beta_k \Delta \text{Aggregate Individual Binary Signal}_q^k + \varepsilon_{q+1}$

Regression with Newey-West standard errors Number of obs = 113
maximum lag: 4 F(3, 109) = 0.87
Prob > F = 0.4596

Δ GDP	Newey-West		t	P> t	[95% Conf. Interval]	
	Coef.	Std. Err.				
Δ BS5_Debt	-.0003131	.0031662	-0.10	0.921	-.0065884	.0059622
Δ BS6_curren~o	.0087583	.0072664	1.21	0.231	-.0056436	.0231601
Δ BS7_Equity	.0031278	.0037187	0.84	0.402	-.0042426	.0104982
_cons	.0109469	.0009549	11.46	0.000	.0090544	.0128394

Table 15:**Regression of** $g_{q+1} = \alpha + \times \beta_1 \Delta \text{Aggregate BS5_Debt}_q + \varepsilon_{q+1}$

Regression with Newey-West standard errors Number of obs = 113
maximum lag: 4 F(1, 111) = 0.00
Prob > F = 0.9893

ΔGDP	Newey-West		t	P> t	[95% Conf. Interval]	
	Coef.	Std. Err.				
$\Delta \text{BS5_Debt}$.0000441	.0032979	0.01	0.989	-.0064909	.0065792
_cons	.0111053	.0008991	12.35	0.000	.0093237	.012887

Table 16:**Regression of** $g_{q+1} = \alpha + \times \beta_1 \Delta \text{Aggregate BS6_Currentratio}_q + \varepsilon_{q+1}$

Regression with Newey-West standard errors Number of obs = 113
maximum lag: 4 F(1, 111) = 0.48
Prob > F = 0.4919

ΔGDP	Newey-West		t	P> t	[95% Conf. Interval]	
	Coef.	Std. Err.				
$\Delta \text{BS6_curren} \sim o$.0061311	.0088912	0.69	0.492	-.0114875	.0237496
_cons	.0110844	.0009132	12.14	0.000	.0092747	.012894

Table 17:**Regression of** $g_{q+1} = \alpha + \times \beta_1 \Delta \text{Aggregate BS7_Equity}_q + \varepsilon_{q+1}$

Regression with Newey-West standard errors Number of obs = 113
maximum lag: 4 F(1, 111) = 0.42
Prob > F = 0.5173

ΔGDP	Newey-West		t	P> t	[95% Conf. Interval]	
	Coef.	Std. Err.				
$\Delta \text{BS7_Equity}$.0024606	.003788	0.65	0.517	-.0050455	.0099668
_cons	.0110013	.0009835	11.19	0.000	.0090524	.0129501

Table 18:**Regression of** $g_{q+1} = \alpha + \gamma * stockmarket\ return_{t-3 \rightarrow t} + \varepsilon_{q+1}$

Regression with Newey-West standard errors Number of obs = 113
maximum lag: 4 F(1, 111) = 3.37
Prob > F = 0.0690

ΔGDP	Newey-West		t	P> t	[95% Conf. Interval]	
	Coef.	Std. Err.				
three_mon_ret	.0243331	.0132523	1.84	0.069	-.0019272	.0505934
_cons	.0105987	.0010251	10.34	0.000	.0085673	.01263

Table 19:**Regression of** $g_{q+1} = \alpha + \gamma * stockmarket\ return_{t-6 \rightarrow t} + \varepsilon_{q+1}$

Regression with Newey-West standard errors Number of obs = 113
maximum lag: 4 F(1, 111) = 7.06
Prob > F = 0.0091

ΔGDP	Newey-West		t	P> t	[95% Conf. Interval]	
	Coef.	Std. Err.				
six_mon_ret	.0237172	.0089274	2.66	0.009	.0060269	.0414074
_cons	.0100947	.0010061	10.03	0.000	.0081011	.0120883

Table 20:**Regression of** $g_{q+1} = \alpha + \gamma * stockmarket\ return_{t-9 \rightarrow t} + \varepsilon_{q+1}$

Regression with Newey-West standard errors Number of obs = 113
maximum lag: 4 F(1, 111) = 8.58
Prob > F = 0.0041

ΔGDP	Newey-West		t	P> t	[95% Conf. Interval]	
	Coef.	Std. Err.				
nine_mon_ret	.0206733	.0070593	2.93	0.004	.0066849	.0346617
_cons	.0097545	.0010357	9.42	0.000	.0077022	.0118067

Table 21:

Regression of $g_{q+1} = \alpha + \gamma * stockmarket\ return_{t-12 \rightarrow t} + \varepsilon_{q+1}$

Regression with Newey-West standard errors Number of obs = 113
maximum lag: 4 F(1, 111) = 8.74
Prob > F = 0.0038

ΔGDP	Newey-West		t	P> t	[95% Conf. Interval]	
	Coef.	Std. Err.				
one_year_ret	.0180695	.0061114	2.96	0.004	.0059593	.0301797
_cons	.0094962	.0011027	8.61	0.000	.0073111	.0116813

Table 22:

Regression of $g_{q+1} = \alpha + \gamma * stockmarket\ return_{t-24 \rightarrow t} + \varepsilon_{q+1}$

Regression with Newey-West standard errors Number of obs = 113
maximum lag: 4 F(1, 111) = 5.41
Prob > F = 0.0218

ΔGDP	Newey-West		t	P> t	[95% Conf. Interval]	
	Coef.	Std. Err.				
two_year_ret	.0082345	.0035406	2.33	0.022	.0012186	.0152503
_cons	.0095371	.0013503	7.06	0.000	.0068613	.0122128

Table 23:

Regression of

$$g_{q+1} = \alpha + \gamma * stockmarket\ return_{t-12 \rightarrow t} + \beta_1 \times \Delta Aggregate\ Total\ FScore_q + \varepsilon_{q+1}$$

Regression with Newey-West standard errors Number of obs = 113
maximum lag: 4 F(2, 110) = 5.23
Prob > F = 0.0067

ΔGDP	Newey-West		t	P> t	[95% Conf. Interval]	
	Coef.	Std. Err.				
$\Delta Total_FScore$.0189967	.0122758	1.55	0.125	-.0053309	.0433244
one_year_ret	.0179769	.0057619	3.12	0.002	.0065582	.0293957
_cons	.0094344	.0010273	9.18	0.000	.0073986	.0114702

Table 24:**Regression of**

$$g_{q+1} = \alpha + \gamma * stockmarket\ return_{t-12 \rightarrow t} + \beta_1 \times \Delta Aggregate\ Liquidity_Leverage\ Partial\ FScore_q + \varepsilon_{q+1}$$

Regression with Newey-West standard errors Number of obs = 113
maximum lag: 4 F(2, 110) = 6.76
Prob > F = 0.0017

ΔGDP	Newey-West					[95% Conf. Interval]	
	Coef.	Std. Err.	t	P> t			
ΔLiq_Lev	.0081351	.0056067	1.45	0.150	-.002976	.0192462	
one_year_ret	.017692	.0060845	2.91	0.004	.0056341	.02975	
$_cons$.0094792	.0010608	8.94	0.000	.0073769	.0115815	

Table 25:**Regression of**

$$E_q[g_{q+1}] - E_{q-1}[g_{q+1}] = \alpha + \gamma * stockmarket\ return_{t-k \rightarrow t} + \beta_1 \times \Delta Aggregate\ Total\ FScore_q + \varepsilon_{q+1}$$

Regression with Newey-West standard errors Number of obs = 113
maximum lag: 4 F(2, 110) = 16.48
Prob > F = 0.0000

F_Revision	Newey-West					[95% Conf. Interval]	
	Coef.	Std. Err.	t	P> t			
$\Delta Total_FScore$.020087	.013963	1.44	0.153	-.0075844	.0477584	
one_year_ret	.0220613	.0040271	5.48	0.000	.0140805	.0300422	
$_cons$	-.0023515	.0008231	-2.86	0.005	-.0039827	-.0007203	

Table 26:Regression of

$$E_q[g_{q+1}] - E_{q-1}[g_{q+1}] =$$

$$\alpha + \gamma * stockmarket\ return_{t-k \rightarrow t} + \beta_1 \times \Delta Aggregate\ Liquidity_Leverage\ Partial\ FScore + \varepsilon_{q+1}$$

Regression with Newey-West standard errors	Number of obs	=	113
maximum lag: 4	F(2, 110)	=	14.30
	Prob > F	=	0.0000

F_Revision	Newey-West		t	P> t	[95% Conf. Interval]	
	Coef.	Std. Err.				
ΔLiq_Lev	.0068167	.0078618	0.87	0.388	-.0087636	.0223969
one_year_ret	.0218429	.0040849	5.35	0.000	.0137477	.0299382
_cons	-.0023004	.0008191	-2.81	0.006	-.0039236	-.0006772

Table 27:Regression of

$$E_q[g_{q+1}] - E_{q-1}[g_{q+1}] = \alpha + \gamma * stockmarket\ return_{t-k \rightarrow t} + \varepsilon_{q+1}$$

Regression with Newey-West standard errors	Number of obs	=	113
maximum lag: 4	F(1, 111)	=	27.08
	Prob > F	=	0.0000

F_Revision	Newey-West		t	P> t	[95% Conf. Interval]	
	Coef.	Std. Err.				
one_year_ret	.0221592	.0042582	5.20	0.000	.0137212	.0305972
_cons	-.0022862	.0008391	-2.72	0.007	-.003949	-.0006233

Table 28:**Regression of**

$$g_{q+1} - E_q[g_{q+1}] = \alpha + \beta_1 \times \Delta \text{Aggregate Total FScore}_q + \varepsilon_{q+1}$$

Regression with Newey-West standard errors Number of obs = 113
maximum lag: 4 F(1, 111) = 1.67
Prob > F = 0.1984

F_Error	Newey-West		t	P> t	[95% Conf. Interval]	
	Coef.	Std. Err.				
$\Delta \text{Total_FScore}$.0336295	.0259912	1.29	0.198	-.0178739	.0851329
_cons	.0007108	.0015318	0.46	0.644	-.0023245	.0037462

Table 29:**Regression of**

$$g_{q+1} - E_q[g_{q+1}] = \alpha + \beta_1 \times \Delta \text{Aggregate Liquidity_Leverage Partial FScore} + \varepsilon_{q+1}$$

Regression with Newey-West standard errors Number of obs = 113
maximum lag: 4 F(1, 111) = 15.60
Prob > F = 0.0001

F_Error	Newey-West		t	P> t	[95% Conf. Interval]	
	Coef.	Std. Err.				
$\Delta \text{Liq_Lev}$.0396919	.0100497	3.95	0.000	.0197778	.059606
_cons	.0005877	.0014078	0.42	0.677	-.0022019	.0033774

Table 30:Regression of

$$g_{q+1} - E_q[g_{q+1}] =$$

$$\alpha + \gamma * stockmarket\ return_{t-k \rightarrow t} + \beta_1 \times \Delta Aggregate\ Liquidity_Leverage\ Partial\ FScore + \varepsilon_{q+1}$$

Regression with Newey-West standard errors	Number of obs	=	113
maximum lag: 4	F(2, 110)	=	25.44
	Prob > F	=	0.0000

F_Error	Newey-West					[95% Conf. Interval]
	Coef.	Std. Err.	t	P> t		
ΔLiq_Lev	.0368243	.0083762	4.40	0.000	.0202246	.0534239
one_year_ret	.01855	.0054834	3.38	0.001	.0076832	.0294168
_cons	-.001047	.0014148	-0.74	0.461	-.0038509	.0017569

Table 31:Regression of

$$g_{q+1} - E_q[g_{q+1}] =$$

$$\alpha + \gamma * stockmarket\ return_{t-k \rightarrow t} + \varepsilon_{q+1}$$

Regression with Newey-West standard errors	Number of obs	=	113
maximum lag: 4	F(1, 111)	=	15.14
	Prob > F	=	0.0002

F_Error	Newey-West					[95% Conf. Interval]
	Coef.	Std. Err.	t	P> t		
one_year_ret	.0202587	.0052073	3.89	0.000	.0099401	.0305772
_cons	-.00097	.0014793	-0.66	0.513	-.0039013	.0019613

Table 32: Dickey Fuller – Generalised Least Squares for Δ BS5 Debt

DF-GLS for Δ BS5_Debt Number of obs = 102

[lags]	DF-GLS tau Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
10	-2.447	-3.564	-2.823	-2.547
9	-2.804	-3.564	-2.848	-2.570
8	-2.513	-3.564	-2.873	-2.593
7	-3.373	-3.564	-2.897	-2.615
6	-2.799	-3.564	-2.919	-2.636
5	-3.134	-3.564	-2.941	-2.656
4	-3.959	-3.564	-2.961	-2.674
3	-6.061	-3.564	-2.980	-2.691
2	-5.125	-3.564	-2.997	-2.707
1	-6.577	-3.564	-3.012	-2.721

Table 33: Dickey Fuller – Generalised Least Squares for Δ BS6 currentratio

DF-GLS for Δ BS6_currentratio Number of obs = 102

[lags]	DF-GLS tau Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
10	-3.680	-3.564	-2.823	-2.547
9	-3.374	-3.564	-2.848	-2.570
8	-3.451	-3.564	-2.873	-2.593
7	-4.902	-3.564	-2.897	-2.615
6	-4.772	-3.564	-2.919	-2.636
5	-4.185	-3.564	-2.941	-2.656
4	-4.558	-3.564	-2.961	-2.674
3	-7.450	-3.564	-2.980	-2.691
2	-4.625	-3.564	-2.997	-2.707
1	-4.039	-3.564	-3.012	-2.721

Table 34: Dickey Fuller – Generalised Least Squares for Δ BS7_EquityDF-GLS for Δ BS7_Equity

Number of obs = 102

[lags]	DF-GLS tau Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
10	-3.187	-3.564	-2.823	-2.547
9	-3.648	-3.564	-2.848	-2.570
8	-3.986	-3.564	-2.873	-2.593
7	-5.150	-3.564	-2.897	-2.615
6	-4.328	-3.564	-2.919	-2.636
5	-3.924	-3.564	-2.941	-2.656
4	-4.168	-3.564	-2.961	-2.674
3	-5.574	-3.564	-2.980	-2.691
2	-4.577	-3.564	-2.997	-2.707
1	-5.412	-3.564	-3.012	-2.721

Table 35: Dickey Fuller – Generalised Least Squares for Δ ProfitabilityDF-GLS for Δ Profitability

Number of obs = 102

[lags]	DF-GLS tau Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
10	-3.122	-3.564	-2.823	-2.547
9	-3.058	-3.564	-2.848	-2.570
8	-3.171	-3.564	-2.873	-2.593
7	-3.704	-3.564	-2.897	-2.615
6	-3.469	-3.564	-2.919	-2.636
5	-3.586	-3.564	-2.941	-2.656
4	-4.201	-3.564	-2.961	-2.674
3	-5.894	-3.564	-2.980	-2.691
2	-4.535	-3.564	-2.997	-2.707
1	-5.160	-3.564	-3.012	-2.721

Table 36: Dickey Fuller – Generalised Least Squares for $\Delta\text{Liq_Lev}$ DF-GLS for $\Delta\text{Liq_Lev}$

Number of obs = 102

[lags]	DF-GLS tau Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
10	-2.621	-3.564	-2.823	-2.547
9	-2.462	-3.564	-2.848	-2.570
8	-2.117	-3.564	-2.873	-2.593
7	-3.385	-3.564	-2.897	-2.615
6	-2.471	-3.564	-2.919	-2.636
5	-2.553	-3.564	-2.941	-2.656
4	-3.508	-3.564	-2.961	-2.674
3	-5.399	-3.564	-2.980	-2.691
2	-3.837	-3.564	-2.997	-2.707
1	-5.248	-3.564	-3.012	-2.721

Table 37: Dickey Fuller – Generalised Least Squares for $\Delta\text{Operational_Eff}$ DF-GLS for $\Delta\text{Operational_Eff}$

Number of obs = 102

[lags]	DF-GLS tau Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
10	-3.904	-3.564	-2.823	-2.547
9	-4.033	-3.564	-2.848	-2.570
8	-4.804	-3.564	-2.873	-2.593
7	-5.038	-3.564	-2.897	-2.615
6	-3.686	-3.564	-2.919	-2.636
5	-4.641	-3.564	-2.941	-2.656
4	-5.926	-3.564	-2.961	-2.674
3	-8.311	-3.564	-2.980	-2.691
2	-5.202	-3.564	-2.997	-2.707
1	-6.815	-3.564	-3.012	-2.721

Table 38: Dickey Fuller – Generalised Least Squares for Δ Total_FScoreDF-GLS for Δ Total_FScore

Number of obs = 102

[lags]	DF-GLS tau Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
10	-2.637	-3.564	-2.823	-2.547
9	-2.399	-3.564	-2.848	-2.570
8	-2.268	-3.564	-2.873	-2.593
7	-2.840	-3.564	-2.897	-2.615
6	-2.508	-3.564	-2.919	-2.636
5	-2.941	-3.564	-2.941	-2.656
4	-3.839	-3.564	-2.961	-2.674
3	-5.243	-3.564	-2.980	-2.691
2	-3.719	-3.564	-2.997	-2.707
1	-5.422	-3.564	-3.012	-2.721

Table 39: Dickey Fuller – Generalised Least Squares for Δ GDPDF-GLS for Δ GDP

Number of obs = 102

[lags]	DF-GLS tau Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
10	-3.029	-3.564	-2.823	-2.547
9	-2.566	-3.564	-2.848	-2.570
8	-2.614	-3.564	-2.873	-2.593
7	-3.131	-3.564	-2.897	-2.615
6	-3.144	-3.564	-2.919	-2.636
5	-3.164	-3.564	-2.941	-2.656
4	-3.474	-3.564	-2.961	-2.674
3	-3.384	-3.564	-2.980	-2.691
2	-3.802	-3.564	-2.997	-2.707
1	-4.362	-3.564	-3.012	-2.721

Table 40: Dickey Fuller – Generalised Least Squares for Δ one_year_ret

DF-GLS for one_year_ret

Number of obs = 102

[lags]	DF-GLS tau Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
10	-3.070	-3.564	-2.823	-2.547
9	-2.782	-3.564	-2.848	-2.570
8	-2.515	-3.564	-2.873	-2.593
7	-3.201	-3.564	-2.897	-2.615
6	-3.224	-3.564	-2.919	-2.636
5	-3.462	-3.564	-2.941	-2.656
4	-2.749	-3.564	-2.961	-2.674
3	-4.416	-3.564	-2.980	-2.691
2	-3.877	-3.564	-2.997	-2.707
1	-3.767	-3.564	-3.012	-2.721

Table 41: Dickey Fuller – Generalised Least Squares for Δ F_Revision

DF-GLS for F_Revision

Number of obs = 102

[lags]	DF-GLS tau Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
10	-3.320	-3.564	-2.823	-2.547
9	-3.238	-3.564	-2.848	-2.570
8	-3.411	-3.564	-2.873	-2.593
7	-4.018	-3.564	-2.897	-2.615
6	-3.653	-3.564	-2.919	-2.636
5	-3.507	-3.564	-2.941	-2.656
4	-4.274	-3.564	-2.961	-2.674
3	-4.097	-3.564	-2.980	-2.691
2	-4.554	-3.564	-2.997	-2.707
1	-6.287	-3.564	-3.012	-2.721

Table 42: Dickey Fuller – Generalised Least Squares for ΔF_Error

DF-GLS for F_Error Number of obs = 102

[lags]	DF-GLS tau Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
10	-2.993	-3.564	-2.823	-2.547
9	-3.300	-3.564	-2.848	-2.570
8	-2.887	-3.564	-2.873	-2.593
7	-3.684	-3.564	-2.897	-2.615
6	-3.844	-3.564	-2.919	-2.636
5	-3.758	-3.564	-2.941	-2.656
4	-3.418	-3.564	-2.961	-2.674
3	-4.522	-3.564	-2.980	-2.691
2	-3.731	-3.564	-2.997	-2.707
1	-6.077	-3.564	-3.012	-2.721

Table 43: Variance Inflation Factor (VIF) for Regression:

$$g_{q+1} = \alpha + \sum \beta_k \times \Delta \text{Aggregate Partial } F\text{Scores}_q^k + \varepsilon_{q+1}$$

Variable	VIF	1/VIF
$\Delta \text{Profitability}$	1.04	0.960082
$\Delta \text{Liq_Lev}$	1.04	0.965707
$\Delta \text{Operation~f}$	1.01	0.989495
Mean VIF	1.03	